# Measuring the impact of natural disasters on capital markets: An empirical application using intervention analysis

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**Abstract**

This paper examines the impact of natural disasters on the Australian equity market. The data set employed consists of daily price and accumulation returns over the period 31 December 1982 to 1 January 2002 for the All Ordinaries Index (AOI) and a record of forty-two severe storms, floods, cyclones, earthquakes and bushfires (wildfires) during this period with an insured loss in excess of AUD5 mil. and/or total loss in excess of AUD100 mil. Autoregressive moving average (ARMA) models are used to model the returns and the inclusion of news arrival in the form of the natural disasters is specified using intervention analysis. The results indicate bushfires, cyclones and earthquakes have a major effect on market returns, unlike severe storms and floods. The net effects can be positive and/or negative with most effects being felt on the day of the event and with some adjustment in the days that follow.

*JEL classification:* C22, G12, G14, G22.

*Keywords:* Natural events, disasters and catastrophes, market returns, intervention analysis, ARMA

## 1. Introduction

In recent years, and for all too understandable reasons, public concern regarding events and disasters of a natural origin has fallen relative to those of human origin. However, natural events and disasters (including floods, storms, bushfires, hurricanes, cyclones, tsunamis and earthquakes) continue to cause severe and increasing damage to global economies. In the United States the average annual loss from natural disasters in the period 1989 to 1993 was USD3.3 billion, and this grew to USD13 billion annually over the four years to 1997 (FEMA 2003). At least part of this increase is attributed to global climate change (and its influence on hurricane, flood and tornado activity) and part to population growth in disaster-prone states (including hurricanes in Florida, North Carolina and Texas and earthquakes in California and Washington). Similarly, in Australia the average annual cost of natural disasters between 1967 and 1999 was AUD1.14 billion (including the cost of deaths and injuries) and there is

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also some evidence that the number and costs of disasters per year are increasing, partly due to better reporting and possibly also to increasing population and infrastructure in vulnerable areas (EMA 2003). Such developments are reflected on a global scale, where economic and financial activity is very often concentrated in areas prone to natural hazards, led most notably by Tokyo, the San Francisco Bay area, the combined Osaka-Kobe-Kyoto mega city and Miami (Anonymous 2003). In response to these developments, an emerging literature has addressed a variety of dimensions regarding the economic and financial impact of natural disasters including Fox (1995, 1996), Skidmore and Toya (2002), Horwich (2000), Albala-Bertrand (2000) and Skidmore (2001).

In brief, the estimated economic costs of natural events and disasters depend on the level at which the analysis is undertaken. At its broadest, and apart from the direct damage caused to those in the affected area, the disruption to supply caused by a natural disaster usually involves the transfer of producer surplus from those enterprises negatively affected to those that are unaffected. As these transfers do not normally comprise economic loss (unless new supply is sourced from imports or the original supply was intended for export, in which case the transfer of producer surplus is from domestic to foreign producers) the economic analysis of natural events and disasters ignores the distributional effects and concentrates on all other impacts affecting any member of society (BTE 2001). These impacts may be both tangible (with market values) and intangible (without market values). In the former, they include direct costs such as the damage to infrastructure, buildings and vehicles and indirect costs from the loss of production, emergency response, relief and clean-up. In the latter, they include the direct costs from death and injury and the destruction of items of cultural and personal significance and indirect costs from inconvenience, social disruption and the stress associated with mortality and illness (BTE 2001). Depending on the type of disaster, it is often found that intangibles comprise the largest part of the total costs of a given event.

In contrast to the economic analysis of natural disasters, financial analysis is concerned solely with the financial impact on those individuals and enterprises directly affected. Markets prices are used to value all costs and benefits and all other impacts outside these entities are ignored. It is within this limited context that most of the existing financial research into natural disasters is placed and which, for the most part, has focused almost primarily on the property-liability insurance industry. Within this industry, two opposing, but not mutually exclusive, hypotheses exist [see AAA (2001) for a discussion of insurance industry catastrophe management practices]. The first and most obvious is that insurers, because of the payments made to policyholders for their damages, incur large losses. While at least some of this is offset by reinsurance, for the most part the expectation is that these losses should cause insurance stocks to decline at the time of the disaster. The less obvious effect is that insurers benefit from an isolated catastrophic event because of increased demand for their products, through an increase in both required coverage and additional premium earnings.

The net effect on property-liability insurer stock values thus varies according to the relative strength of these two opposing forces. Shelor *et al*. (1992) and Aiuppa *et al*. (1993), for example, both concluded that insurer stock values increased after California's Loma Prieta earthquake [insured loss USD2.5 billion] in part because high earthquake insurance rates and low perceived risk meant many property owners were uncovered at the time. Conversely, Angbazo and Narayanan (1996) and Lamb (1995) found that the large negative effect of Florida and Louisiana's Hurricane Andrew [insured loss USD16.5 billion] was only slightly offset by the subsequent premium increases, and furthermore that the event even showed evidence of a contagion effect to insurers with no claims exposure in the hurricane affected states. Lastly, Cagle (1996) concluded that South Carolina's Hurricane Hugo [insured loss USD4.2 billion] caused a significant negative price reaction for insurers with high exposure and unaffected those with low exposure. The issue of property catastrophe risk and insurance/reinsurance is discussed at length in Borden and Sarker (1996), Jones (1999) and Anderson (2000).

It is clear, even putting aside the intrinsically narrow focus of financial analysis into natural events and disasters, that existing research suffers a number of limitations. First and foremost, there is the concentration on the property liability insurance industry even though it is well known that natural events and disasters have a substantial, often positive, impact on non-insurance firms (BTE 2001, FMA 2003, EMA 2003). For instance, Skidmore and Toya (2002) discuss how the impact of natural disasters is normally felt first in the loss of capital and durable goods and that efforts to replace them (such as by the construction and manufacturing industries) often increase economic output. Moreover, insured losses always underestimate total losses by a significant margin. For example, in Australia the proportion of insured to total loss is 35 percent for severe storms and bushfires, 25 percent for earthquakes, 20 percent for tropical cyclones and as little as 10 percent for floods (BTE 2001). No study exists in the Australian context which examines the impact of natural events and disasters across an entire market.

Second, nearly all past studies of the financial impact of natural events and disasters have tended to employ a single event study. While this simplifies the analysis, it is problematic in that single events may be susceptible to contamination by macroeconomic events independent of the disaster or catastrophe itself. For example, West (2003) argues that the Shelor *et al.* (1992) analysis of the 1989 Loma Prieta earthquake was compromised because it failed to take account of the lowering of official US interest rates two days later. Even so, the distinction (usually on the basis of insured cost) between natural 'catastrophes', 'disasters' and 'events' is arbitrarily made and often ignores the fact that even relatively 'small' episodes can have important financial impacts. This is especially the case where a series of such events and disasters occur in quick succession. Unfortunately, no evidence currently exists on how the ongoing sequence of natural events and disasters, both large and small, impacts upon market behaviour. Moreover, there is no known study that examines the impact conjointly of the many types of natural disasters posited to have a financial impact, including earthquakes, tornados, hurricanes, severe storms and fires.

Accordingly, the purpose of this paper is to model the market impacts of natural disasters in Australia. This is believed to be the first financial study of natural disasters to use intervention analysis in an autoregressive moving average (ARMA) framework, and one of few studies of the financial impacts of natural disasters outside the United States. The paper itself is divided into four main areas. The second section explains the data employed in the analysis and presents some summary statistics. The third section discusses the methodology employed. The results are dealt with in the fourth section. The paper ends with some brief concluding remarks.

## 2. Data and summary statistics

Two sets of data are employed in the analysis. The first set of data is the daily closing price for the Australian Stock Exchange (ASX) All Ordinaries index (AOI) over the period 1 January 1983 to 1 January 2002. The AOI is a market-weighted index and currently accounts for ninety-six percent of the market capitalization of domestic equities listed in Australia. The criteria for inclusion in the index place an emphasis on liquidity and investability and together the high frequency of information arrivals and volume of trading in these securities are likely to reduce measurement error problems. All data are obtained electronically from Bloomberg. The natural log of the relative price is computed for the 4,957 closing prices to produce a time series of continuously compounded daily returns, such that $r_t = \log(p_t/p_{t-1})\text{x}100$, where $p_t$ and

$p_{t-1}$ represent the market price at time $t$ and $t$-1, respectively. Both the AOI price and accumulation (including dividends and capitalisation changes) indices are used yielding a daily price (*PRR*) and accumulation (*ACR*) returns series.

<TABLE 1 HERE>

The second set of data is sourced from Emergency Management Australia (EMA). EMA (2003) provides a database that is a record of Australian natural disasters compiled using estimates from insurance industry bodies, published disaster reports and articles in newspapers and other media. The database relies heavily on media reports and therefore the consistency of the media's approach and its definitions as to what constitutes a newsworthy event are a major limitation (BTE 2001). Nevertheless, the database is believed to constitute the most complete record of natural disasters in Australia. From this complete set of events, disasters and catastrophes, forty-two 'significant' events were selected on the basis that they had an insured loss greater than AUD5 mil. and/or total loss greater than AUD100 mil. Selected descriptive statistics for these natural disasters are presented in Table 2.

Five major categories of disaster are identified from the most common forms of natural events and disasters in Australia. These are: (i) severe storms (including hail) (*STM*); (ii) floods (including flash floods) (*FLD*); (iii) tropical cyclones (including tornados and sea spouts) (*CYC*); (iv) bushfires (or wildfires) (*BSH*); and (v) earthquakes (including landslides) (*EQK*). Generally floods (28.9 percent of average annual cost) are the most costly and frequent disaster type in Australia, followed by severe storms (26.2 percent) and tropical cyclones (24.5 percent). Though bushfires are also frequent they are generally less costly (7.1 percent), but more hazardous in terms of deaths and injuries, while earthquakes are less frequent but have been significant in terms of costs (13.3 percent) largely through two single events (the 1989 Newcastle earthquake and the 1997 Thredbo landslide) (BTE 2001). The other disaster categories also include relatively more costly single events, such as the Sydney hailstorm and Ash Wednesday bushfires. The duration of these events vary, with earthquakes and, to a lesser extent, cyclones and severe storms confined to a single day, while bushfires and floods occur over several days, weeks or even months. The dates included in the analysis are those when substantial loss was first deemed likely.

<TABLE 2 HERE>

Table 1 presents the descriptive statistics of the daily market returns. Sample means, standard deviations, skewness, kurtosis and the Jacque-Bera statistic and $p$-value are reported. By and large, the distributional properties of both price and accumulation returns appear non-normal. Both are negatively skewed (-5.9520 and -5.9125), indicating the greater probability of large deceases in returns than rises (that is, volatility clustering in daily returns). Given the asymptotic sampling distribution of skewness is normal with mean 0 and standard deviation of $\sqrt{6/T}$ , where $T$ is the sample size, for a sample size of 4,958 the standard error under the null hypothesis of normality is 0.0348: the estimates of skewness are significant at the .01 level. The kurtosis, or degree of excess, in both return series is also large (166.5038 and 165.7662), thereby indicating leptokurtic distributions. Since the sampling distribution of kurtosis is normal with mean 0 and standard deviation of $\sqrt{24/T} = 0.0695$ the estimates are once again statistically significant at any conventional level.

The Jarque-Bera statistics and corresponding $p$-values in Table 1 are used to test the null hypotheses that the daily distribution of market returns is normally distributed. Both $p$-values are smaller than the .01 level of significance suggesting the null hypothesis can be rejected. These stock market returns are then not well approximated by the normal distribution. Unit root tests are conducted in Table 1 as a means of elaborating upon the time series properties of the return series. The ADF $t$-statistics reject the null hypotheses of a unit root at the .01 level, For the KPSS tests of the null hypothesis of no unit root, the $LM$-statistic fails to exceed the asymptotic critical value also at the .01 level. We may conclude that both return series examined are stationary.

## 3. Model specification

Since the time series data on price and accumulation returns are available in regularly spaced intervals and given the timing of the natural disasters is known with certainty, intervention analysis can be used to examine the impact and duration of impact of natural disasters on the Australian capital market. Intervention analysis is based on the Box-Jenkins methodology in which an autoregressive moving average (ARMA) model is augmented by dummy variables to evaluate the effect(s) of extraordinary or abnormal events. Since first proposed by Box and Tiao (1975) this technique has been employed in a variety of financial contexts. For example, Ho and Wan (2002) used intervention analysis to test for structural breaks following the 1997 Asian financial crisis, Liu and Yu (2002) investigated the role of Taiwan's stock stabilization fund in countering market declines associated with foreign policy changes and Bhar (2001) and St. Pierre (1998) used it to examine the return and volatility dynamics of the Australian spot and futures markets and the volatility impacts of introducing option contracts, respectively. Likewise, intervention analysis has also found application in studies of natural disasters with Fox's (1995, 1996) examination of the impact of Hurricane Hugo on business environments.

The following ARMA process of order ($k$,$q$) is specified (assuming stationary daily returns):

$$\Phi_k(L)(1-\phi L^r)y_t = \mu + \Theta_q(L)\varepsilon_t + \beta D_t \tag{1}$$

where $\Phi_k(L)$ represents a $k$-order polynomial lag operator, $\phi$ is a seasonal parameter, $r$ is the seasonal lag term, $y$ represents the market return in price or accumulation form, $\mu$ is a constant, $\Theta_q(L)$ denotes a $q$-order polynomial lag operator, $\varepsilon$ is a white noise process, $k$ is the number of autoregressive (AR) terms, $q$ is the number of moving-average (MA) terms and $D_t$ are intervention dummy variables.

Three important specification issues arise in this model. First, as part of the modeling process one needs first to choose accurate values for $k$, $r$ and $q$ in the ARMA specification. While the identification of an appropriate ARMA model is not exact, as a rule of thumb the autocorrelation (AC) and partial autocorrelation (PAC) functions can be used to determine $q$ and $k$, respectively. The estimated model is then subjected to a range of diagnostic checks on the residuals to ensure that the model has properly accounted for all systematic variation in the time series. Second, the ARMA model specified should also capture any systematic underlying time series patterns in the data (of which seasonality is the most obvious). This is important since systematic time series patterns in the fluctuations in the data need to be accounted for so as to accurately gauge the impact of the natural disasters. In order to address this possibility, equation (1) is augmented by a seasonal autoregressive term (Box *et al.* 1994). Lastly, it is also important under ARMA theory that the series being modeled is stationary. As shown in Table 1 unit root tests for the price and market return series indicate stationarity. The general form of the equation used to model market returns is then as follows:

$$(1-\rho_1 L-\rho_2 L^2-\ldots\rho_k L^k)(1-\phi L^r)y_t = \mu_0 + \Theta_q(L)\varepsilon_t + \sum\nolimits_{g=1}^{2}\gamma_g Du_{gt} + \sum\nolimits_{i=1}^{n=5}\sum\nolimits_{j=0}^{m=5}\beta_{ij}D_{it-j} + w_t \tag{2}$$

Where $\rho_s$ are autoregressive parameters, $\gamma_1$ and $\gamma_2$ are macroeconomic intervention parameters to be estimated (as below), and all other variables are as previously defined.

Two sets of intervention variables are included in (2). First, a visual inspection of plots of the price and accumulation return series (not shown) over the period indicates the presence of several outliers: all of which correspond to macroeconomic incidents unrelated to natural disasters. The most significant event corresponds to 20 October 1987 when the AOI fell by a one-day record 29 percent, however ten other declines are found on 23, 26-29 October 1987, 4, 10 November 1987, 16 October 1989, 6 November 1989, 6 November 1997 and 17 April 2000. Dummy variables are used to capture these outliers in daily returns as a means of preventing possible misspecification: $Du_{1t}$ for 20 October 1987 and $Du_{2t}$ for 23, 26, 27, 29 October 1987, 4 and 10 November 1987, 16 October 1989, 6 November 1989, 6 November 1997, and 17 April 2000. As an alternative these observations could be excluded from the sample, however this would lead to the loss of continuity in the time series.

The second set of intervention variables relate to the categories of natural disasters presented in Table 2. For days in which a natural disaster event occurs the 'pulse' dummy variable $D_{it-j}$, takes the value of one and zero elsewhere for $i$ =1, 2…5 where bushfire ($i$ = 1), cyclone ($i$ = 2), earthquake ($i$ = 3), storm ($i$ = 4) and flood ($i$ = 5). Where $j$ = 0 the intervention dummy indicates whether the natural disaster has an immediate and temporary impact on price and/or accumulation returns on the day on which the event occurs. The magnitude and sign of the estimated coefficients on these variables indicates the mean effect of each natural disaster category on market return beyond what could have been expected from the discernible systematic pattern of data fluctuations in the ARMA model. The sign on the estimated coefficients will, of course, depend on the net impact of each type of natural disaster upon the market. In studies of the property-liability insurance sector the stock impact represents the interplay between the negative effect of large loan losses associated with claims by policyholders and the positive effect of higher premium earnings. However, across an entire market the net market impact will depend upon not only the positive and negative effects on the insurance industry alone but also positive impacts associated with reconstruction and rebuilding and negative impacts associated with the disruption to production, amongst others. No particular sign on the estimated coefficients is then hypothesized.

However, there is the real possibility that the natural disaster effect may persist beyond the day of the event itself. Persistence in this model may be related to difficulty in ascertaining the likely losses associated with the natural disaster, lags in information dissemination from the disaster area or delays in forecasting the possible financial effects for firm, industries and the market as a whole. The persistence or duration of these effects is then a matter of empirical investigation, which can be examined by testing the statistical significance of additional (lagged) dummy variables $D_{it-j}$ where $j \geq 1$. To examine persistence in the natural disaster effect for up to six days, five further pulse dummies ($j$ = 1,2…5) are specified in each category to capture the fleeting (subsequent) effects through time. Given the assumed mean reverting process in the Australian market returns, it is hypothesized that the natural disaster effects will be all or nearly all exhausted after six days.

## 4. Empirical results

The estimated coefficients, standard errors and *p*-values of the parameters for the ARMA regression model are provided in Table 3. The estimated coefficients and standard errors employing the entire set of intervention variables where market returns are specified in price terms are shown in Table 3 columns 1 to 3. A refined version of this specification is detailed in columns 4 to 6. The next two sets of estimated coefficients and standard errors in Table 3 relate to additional models where market returns are specified in terms of accumulation returns: a full specification in columns 7 to 9 and a refined specification in columns 10 to 12. Also included in Table 3 are statistics for adjusted $R^2$ and the Schwartz specification criterion (SC) as guides for model specification, and the Durbin-Watson (DW) Ljung-Box (Q) and Breusch-Godfrey Lagrange multiplier (LM) test statistics for first and higher-order serial correlation in the residuals.

<TABLE 3 HERE>

The results in these models appear sensible in terms of both the precision of the estimates and the signs on the coefficients. An ARMA (3,2) error process is found to generate a statistically acceptable model: that is, an autoregressive and moving average error process based on 1-3 and 1-2 day lagged residuals respectively sufficiently account for systematic variation in returns. The ARMA intervention models also pass the conventional diagnostic tests. The DW statistic, especially in the absence of lagged dependent variables in the regression model, is strongly suggestive of no first-order serial correlation. Moreover, the *Q*-statistics (up to 36 lags) and the *LM* (for 5, 10 and 15 lags) fail to reject the null hypotheses of no higher-order serial correlation and the autocorrelations and partial autocorrelations of the innovations in the ARMA models in Table 4 (refined models only) are all nearly zero with insignificant Q-statistics and large p-values. All estimated coefficients for the seasonal $\phi$, autoregressive $\rho$ and moving average $\theta$ terms are also statistically significant and the inverted AR and MA roots (not shown) have modulus less than one, indicating that the estimated ARMA models are stationary. Combined together, these tests indicate that no important forecasting power has been overlooked.

<TABLE 4 HERE>

In the full specification for price returns the estimated coefficients for bushfires with zero, one and four day lags, cyclones with a two and five day lags and earthquakes with a zero and five day lag are significant at the 5 percent level of significance or lower. The estimated coefficients in the full specification indicate that bushfires are associated with small positive effects on the day of and following an event, while cyclones and earthquakes have a small negative effect of less than one percent on the day of the event and a small negative and positive effect respectively five days later. The most significant initial market effects are for cyclones (-0.0095), followed by bushfires (0.0085) and then earthquakes (-0.0043). None of the estimated coefficients for floods or storms are significant at any conventional level. Table 5 include $F$-statistics and $p$-values of the joint null hypotheses that all coefficients for the $i$th natural disaster category are zero across all $j$ lags. The null hypothesis of joint insignificance is rejected for bushfires, cyclones and earthquakes at the .01 level.

These results are generally consistent with those obtained in the refined specification using a Wald criterion for price returns. The signs and magnitudes of the significant estimated bushfire, cyclone and earthquake coefficients are comparable to those found earlier. Wald tests of the joint insignificance of the excluded lag variables for these natural disaster categories are also conducted and the results presented in Table 5. As shown, the null hypotheses of the joint insignificance of the lagged invention variables for bushfires ($j$ = 2, 3 and 5), cyclones ($j$ = 0, 1, 3 and 4) and earthquakes ($j$ = 1, 2, 3 and 4) fail to be rejected. We may conclude that the impact of bushfires on market returns is restricted to the day of and the day following the event, cyclones to two and five days following the event and earthquakes to the day of and five days following the event. No immediate or fleeting effect is observed for storms and floods.

<TABLE 5 HERE>

In general, the results of the full and refined specification where market returns are defined in accumulation terms (including dividend and capitalisation changes) are little different from those in the earlier price return equations. This would indicate that the impact of natural disasters upon the Australian equity market is largely confined to short-term adjustments. The major findings are then as follows. First, bushfires have an overall significant positive effect on market returns that are, on average, noticeable during the first two days or after four days. On average, bushfires are associated with a positive impact of between 0.79 and 0.86 percent on the day of the event and between 0.44 and 0.54 percent in the days following. Second, and unlike bushfires, cyclones adversely affected market returns after two and five days. The estimated models indicate that cyclones are associated with an initial or immediate fall of between 0.97 and 0.98 percent on the day of the event, with a negative adjustment of 0.25 percent five days later.

Third, major earthquakes in Australia have a mixed impact on market returns. Earthquakes immediately exert a significant negative impact of between 0.38 and 0.47 percent on the day when these event strikes, but after five days market returns (however defined) increase by some 0.60 percent. Finally, and as a collateral research outcome, the estimated intervention models adequately capture the calculated October 1987 market fall of 29 percent with estimated coefficients of between -28.21 and -28.34. This is indication that these relatively simple models are capable of measuring the impact of abnormal events in conjunction with systematic time series patterns.

## 5. Concluding remarks

This study presents an analysis of the impact of natural events and disasters on the Australian capital market. The data employed consists of daily price and accumulation returns for the market index over the period 31 December 1982 to 1 January 2002. Intervention (or impact) analysis based an autoregressive integrated moving average (ARIMA) models augmented with dummy variables are used to evaluate the effect of these extraordinary or abnormal events. The most important result of this study is that the shocks provided by natural events and disasters have an influence on market returns. All other things being equal, cyclones, bushfires and earthquakes all exert an influence on returns in the Australian market, of which cyclones and bushfires are generally the most significant. Moreover, these influences vary across time. The obvious argument is that the information represented by these events and disasters is relatively incomplete at the time of the event and, depending on the type of natural disaster, may take some days before a fuller information set is obtained.

Of course, there are several ways in which this work could be extended. One way is to take greater account of the fact that the financial impact of natural events and disasters will clearly vary according to their precise economic impact. In this manner, a focus on a smaller number of major disasters and catastrophes may indicate more significant financial influences, particularly if compared across regions, sectors, industries and companies. Another extension would be to compare impacts across national markets. A sizeable amount of literature already exists in the United States and a comparison between these markets would indicate whether the posited natural disaster effect is confined to smaller, less liquid markets as in Australia or has the ability to impact upon major global economies.

Finally, while it is now the case that better meteorological forecasting and emergency management is helping to mitigate a little of the adverse effects of some natural disasters, disasters of a human origin (especially terrorism in the form of the September 11, Bali and Jakarta terrorist attacks), are deplorably increasing in frequency and severity. It is important for financial regulators and policymakers, both nationally and internationally, to cooperate, communicate and create disaster recovery plans that can be put in place to provide a quick, effective and flexible response to these events. Research attention directed at disasters of a human origin more generally may assist this process.

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TABLE 1 *Summary statistics of price and accumulation returns*

| | | Price | Accumulation |
|---|---|---|---|
| Observations | | 4958 | 4958 |
| Mean | | 0.0004 | 0.0005 |
| Standard deviation | | 0.0097 | 0.0097 |
| Maximum | | 0.0607 | 0.0622 |
| Minimum | | -0.2876 | -0.2875 |
| Skewness | | -5.9520 | -5.9125 |
| Kurtosis | | 166.5038 | 165.7662 |
| Jarque-Bera statistic | | 5551967 | 5501866 |
| JP *p*-value | | 0.0000 | 0.0000 |
| ADF statistic | Constant only | -24.0250 | -24.0939 |
| | Constant and trend | -24.0544 | -24.1262 |
| | Critical value .10 level | -2.5670 | -2.5670 |
| | Critical value .05 level | -2.8619 | -2.8619 |
| | Critical value .01 level | -3.4315 | -3.4315 |
| KPSS statistic | Constant only | 0.1657 | 0.1731 |
| | Constant and trend | 0.0567 | 0.0530 |
| | Critical value .10 level | 0.3470 | 0.3470 |
| | Critical value .05 level | 0.4630 | 0.4630 |
| | Critical value .01 level | 0.7390 | 0.7390 |

Notes: This table provides measures of central tendency, dispersion and shape for the daily price and accumulation returns on the All Ordinaries Index (AOI). The sample period is from 31 December 1982 – 1 January 2002. The critical values of significance for skewness and kurtosis at the .05 level are 0.0681 and 0.1363, respectively, JB – Jarque-Bera. Augmented Dickey-Fuller (ADF) tests hypotheses are $H_0$: unit root, $H_1$: no unit root (stationary). The lag orders in the ADF equations are determined by the significance of the coefficient for the lagged terms. Optimal lag is six for both price and accumulation returns. Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root test hypotheses are $H_0$: no unit root (stationary), $H_1$: unit root.

TABLE 2 *Australian natural disasters by date, 1983-2002*

| Event category | Event date | Persons killed | | Insured loss | | Total loss | | Insured to total loss | |
|---|---|---|---|---|---|---|---|---|---|
| | | No. | Rank | Value | Rank | Value | Rank | % | Rank |
| Bushfire | 16-Feb-83 | 75 | 1 | 324 | 4 | 960 | 3 | 34 | 14 |
| Flood | 12-Nov-94 | 0 | 30 | 132 | 8 | 550 | 6 | 24 | 26 |
| Bushfire | 14-Jan-85 | 5 | 9 | 6 | 41 | 100 | 38 | 6 | 40 |
| Storm | 18-Jan-85 | 1 | 18 | 299 | 5 | 420 | 7 | 71 | 2 |
| Cyclone | 1-Feb-86 | 3 | 12 | 65 | 15 | 300 | 11 | 22 | 28 |
| Flood | 5-Aug-86 | 6 | 6 | 53 | 18 | 270 | 14 | 20 | 30 |
| Storm | 3-Oct-86 | 0 | 30 | 161 | 7 | 255 | 15 | 63 | 5 |
| Flood | 24-Apr-88 | 0 | 30 | 36 | 29 | 230 | 17 | 16 | 34 |
| Cyclone | 4-Apr-89 | 1 | 18 | 35 | 31 | 175 | 23 | 20 | 29 |
| Earthquake | 28-Dec-89 | 13 | 3 | 1124 | 2 | 4500 | 1 | 25 | 25 |
| Cyclone | 3-Feb-90 | 6 | 6 | 42 | 21 | 230 | 17 | 18 | 31 |
| Storm | 18-Mar-90 | 0 | 30 | 384 | 3 | 560 | 5 | 69 | 3 |
| Flood | 21-Apr-90 | 7 | 4 | 38 | 25 | 410 | 8 | 9 | 38 |
| Cyclone | 23-Dec-90 | 6 | 6 | 62 | 16 | 385 | 10 | 16 | 33 |
| Storm | 21-Jan-91 | 1 | 18 | 226 | 6 | 670 | 4 | 34 | 15 |
| Flood | 16-Dec-91 | 0 | 30 | 24 | 36 | 105 | 37 | 23 | 27 |
| Storm | 12-Feb-92 | 0 | 30 | 118 | 9 | 220 | 19 | 54 | 6 |
| Flood | 3-Oct-93 | 1 | 18 | 12 | 38 | 400 | 9 | 3 | 41 |
| Bushfire | 29-Dec-93 | 4 | 11 | 58 | 17 | 175 | 23 | 33 | 19 |
| Cyclone | 23-May-94 | 2 | 15 | 37 | 26 | 115 | 33 | 32 | 21 |
| Storm | 25-May-94 | 0 | 30 | 37 | 26 | 135 | 27 | 27 | 23 |
| Earthquake | 6-Aug-94 | 0 | 30 | 36 | 29 | 140 | 26 | 26 | 24 |
| Cyclone | 23-Feb-95 | 7 | 4 | 11 | 39 | 100 | 38 | 11 | 36 |
| Storm | 5-Nov-95 | 1 | 18 | 40 | 22 | 110 | 35 | 36 | 10 |
| Flood | 1-May-96 | 5 | 9 | 31 | 34 | 240 | 16 | 13 | 35 |
| Storm | 29-Sep-96 | 0 | 30 | 104 | 10 | 300 | 11 | 35 | 13 |
| Flood | 15-Nov-96 | 1 | 18 | 20 | 37 | 120 | 30 | 17 | 32 |
| Storm | 11-Dec-96 | 1 | 18 | 50 | 19 | 150 | 25 | 33 | 17 |
| Earthquake | 30-Jul-97 | 18 | 2 | 11 | 39 | 100 | 38 | 11 | 36 |
| Storm | 19-Dec-97 | 1 | 18 | 40 | 22 | 100 | 38 | 40 | 7 |
| Flood | 10-Jan-98 | 2 | 15 | 69 | 14 | 210 | 20 | 33 | 20 |
| Flood | 26-Jan-98 | 3 | 12 | 70 | 13 | 200 | 22 | 35 | 11 |
| Flood | 17-Aug-98 | 1 | 18 | 50 | 19 | 130 | 28 | 38 | 8 |
| Storm | 16-Dec-98 | 0 | 30 | 76 | 12 | 115 | 33 | 66 | 4 |
| Cyclone | 22-Mar-99 | 0 | 30 | 35 | 31 | 120 | 30 | 29 | 22 |
| Storm | 14-Apr-99 | 1 | 18 | 1700 | 1 | 2300 | 2 | 74 | 1 |
| Storm | 24-Oct-99 | 1 | 18 | 35 | 31 | 100 | 38 | 35 | 11 |
| Flood | 6-Mar-01 | 1 | 18 | 25 | 35 | 300 | 11 | 8 | 39 |
| Storm | 9-Mar-01 | 0 | 30 | 37 | 26 | 110 | 35 | 34 | 16 |
| Storm | 18-Nov-01 | 3 | 12 | 40 | 22 | 120 | 30 | 33 | 17 |
| Storm | 3-Dec-01 | 2 | 15 | 3 | 42 | 130 | 28 | 2 | 42 |
| Bushfire | 12-Dec-01 | 0 | 30 | 80 | 11 | 210 | 20 | 38 | 9 |

*Source*: Emergency Management Australia (2003). *Notes*: This table details all natural events, disasters and catastrophes occurring in Australia over the period 1983-2002 satisfying the size criteria. The conditions set for inclusion is AUD5 mil. insured loss and/or AUD100 total loss. The dates given are actual dates when substantial loss was first known. Disaster categories are: (i) bushfires (wildfires), (ii) tropical cyclones (including tornados and sea spouts), (iii) earthquakes (including landslides), (iv) severe storms (including hail) and (v) floods (including flash floods). Ranks in descending order. Insured loss to total loss is the ratio of insured losses to estimated total losses.

TABLE 3 *Estimated equations for price and accumulation returns*

| | Price returns - full specification | | | Price returns - refined specification | | | Accumulation returns - full specification | | | Accumulation returns - refined specification | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std. error | $p$-value | Coefficient | Std. error | $p$-value | Coefficient | Std. error | $p$-value | Coefficient | Std. error | $p$-value |
| $\mu_0$ | 0.0006 | 0.0001 | 0.0001 | 0.0006 | 0.0001 | 0.0000 | 0.0007 | 0.0001 | 0.0000 | 0.0007 | 0.0001 | 0.0000 |
| $\gamma_1$ | -0.2821 | 0.0035 | 0.0000 | -0.2821 | 0.0034 | 0.0000 | -0.2835 | 0.0028 | 0.0000 | -0.2834 | 0.0025 | 0.0000 |
| $\gamma_2$ | -0.0616 | 0.0081 | 0.0000 | -0.0616 | 0.0080 | 0.0000 | -0.0540 | 0.0097 | 0.0000 | -0.0540 | 0.0097 | 0.0000 |
| $\beta_{10}$ | 0.0085 | 0.0027 | 0.0015 | 0.0086 | 0.0027 | 0.0013 | 0.0087 | 0.0026 | 0.0009 | 0.0079 | 0.0027 | 0.0039 |
| $\beta_{11}$ | 0.0055 | 0.0019 | 0.0043 | 0.0054 | 0.0020 | 0.0055 | 0.0051 | 0.0020 | 0.0100 | 0.0051 | 0.0019 | 0.0076 |
| $\beta_{12}$ | -0.0006 | 0.0029 | 0.8421 | – | – | – | -0.0007 | 0.0030 | 0.8267 | – | – | – |
| $\beta_{13}$ | -0.0047 | 0.0061 | 0.4399 | – | – | – | -0.0049 | 0.0059 | 0.4056 | – | – | – |
| $\beta_{14}$ | 0.0042 | 0.0019 | 0.0239 | 0.0052 | 0.0019 | 0.0054 | 0.0045 | 0.0019 | 0.0165 | 0.0044 | 0.0018 | 0.0148 |
| $\beta_{15}$ | -0.0003 | 0.0048 | 0.9541 | – | – | – | -0.0006 | 0.0048 | 0.9070 | – | – | – |
| $\beta_{20}$ | -0.0008 | 0.0023 | 0.7362 | – | – | – | -0.0005 | 0.0024 | 0.8397 | – | – | – |
| $\beta_{21}$ | 0.0015 | 0.0014 | 0.2882 | – | – | – | 0.0013 | 0.0014 | 0.3717 | – | – | – |
| $\beta_{22}$ | -0.0095 | 0.0022 | 0.0000 | -0.0098 | 0.0022 | 0.0000 | -0.0093 | 0.0022 | 0.0000 | -0.0097 | 0.0022 | 0.0000 |
| $\beta_{23}$ | 0.0028 | 0.0027 | 0.3011 | – | – | – | 0.0029 | 0.0027 | 0.2741 | – | – | – |
| $\beta_{24}$ | -0.0009 | 0.0019 | 0.6406 | – | – | – | -0.0008 | 0.0019 | 0.6699 | – | – | – |
| $\beta_{25}$ | -0.0026 | 0.0012 | 0.0326 | -0.0025 | 0.0012 | 0.0368 | -0.0026 | 0.0013 | 0.0383 | -0.0025 | 0.0012 | 0.0359 |
| $\beta_{30}$ | -0.0043 | 0.0009 | 0.0000 | -0.0047 | 0.0010 | 0.0000 | -0.0035 | 0.0015 | 0.0205 | -0.0038 | 0.0015 | 0.0121 |
| $\beta_{31}$ | 0.0010 | 0.0010 | 0.3158 | – | – | – | 0.0012 | 0.0011 | 0.2496 | – | – | – |
| $\beta_{32}$ | -0.0033 | 0.0021 | 0.1198 | – | – | – | -0.0034 | 0.0020 | 0.0906 | – | – | – |
| $\beta_{33}$ | -0.0025 | 0.0032 | 0.4340 | – | – | – | -0.0027 | 0.0032 | 0.3945 | – | – | – |
| $\beta_{34}$ | 0.0064 | 0.0080 | 0.4259 | – | – | – | 0.0063 | 0.0079 | 0.4239 | – | – | – |
| $\beta_{35}$ | 0.0067 | 0.0030 | 0.0251 | 0.0059 | 0.0028 | 0.0379 | 0.0068 | 0.0030 | 0.0227 | 0.0060 | 0.0028 | 0.0327 |
| $\beta_{40}$ | 0.0014 | 0.0015 | 0.3572 | – | – | – | 0.0015 | 0.0017 | 0.3690 | – | – | – |
| $\beta_{41}$ | -0.0002 | 0.0019 | 0.9084 | – | – | – | -0.0002 | 0.0017 | 0.9071 | – | – | – |
| $\beta_{42}$ | -0.0007 | 0.0019 | 0.7078 | – | – | – | 0.0014 | 0.0023 | 0.5524 | – | – | – |
| $\beta_{43}$ | 0.0000 | 0.0014 | 0.9983 | – | – | – | -0.0002 | 0.0015 | 0.9039 | – | – | – |
| $\beta_{44}$ | 0.0011 | 0.0020 | 0.5751 | – | – | – | 0.0009 | 0.0020 | 0.6299 | – | – | – |
| $\beta_{45}$ | 0.0018 | 0.0016 | 0.2574 | – | – | – | 0.0007 | 0.0012 | 0.5808 | – | – | – |
| $\beta_{50}$ | -0.0011 | 0.0021 | 0.5835 | – | – | – | -0.0023 | 0.0021 | 0.2749 | – | – | – |
| $\beta_{51}$ | 0.0010 | 0.0023 | 0.6612 | – | – | – | 0.0025 | 0.0020 | 0.2206 | – | – | – |
| $\beta_{52}$ | 0.0006 | 0.0028 | 0.8388 | – | – | – | 0.0019 | 0.0029 | 0.5116 | – | – | – |
| $\beta_{53}$ | 0.0002 | 0.0021 | 0.9167 | – | – | – | 0.0002 | 0.0016 | 0.8840 | – | – | – |
| $\beta_{54}$ | -0.0029 | 0.0021 | 0.1639 | – | – | – | 0.0003 | 0.0015 | 0.8313 | – | – | – |

| | Price returns - full specification | | | Price returns - refined specification | | | Accumulation returns - full specification | | | Accumulation returns - refined specification | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std. error | $p$-value | Coefficient | Std. error | $p$-value | Coefficient | Std. error | $p$-value | Coefficient | Std. error | $p$-value |
| $\beta_{55}$ | -0.0035 | 0.0025 | 0.1571 | – | – | – | -0.0030 | 0.0023 | 0.2042 | – | – | – |
| $\rho_1$ | 0.3184 | 0.0507 | 0.0000 | 0.3144 | 0.0502 | 0.0000 | 0.3137 | 0.0575 | 0.0000 | 0.3161 | 0.0444 | 0.0000 |
| $\rho_2$ | -0.9273 | 0.0365 | 0.0000 | -0.9285 | 0.0356 | 0.0000 | -0.9246 | 0.0418 | 0.0000 | -0.9587 | 0.0313 | 0.0000 |
| $\rho_3$ | 0.1232 | 0.0222 | 0.0000 | 0.1229 | 0.0221 | 0.0000 | 0.1086 | 0.0239 | 0.0000 | 0.1122 | 0.0228 | 0.0000 |
| $\phi$ | 0.0326 | 0.0184 | 0.0766 | 0.0323 | 0.0183 | 0.0771 | 0.0283 | 0.0181 | 0.1008 | - | - | - |
| $\theta_l$ | -0.2017 | 0.0458 | 0.0000 | -0.1975 | 0.0452 | 0.0000 | 0.8723 | 0.0467 | 0.0000 | 0.9138 | 0.0364 | 0.0000 |
| $\theta_2$ | 0.8728 | 0.0413 | 0.0000 | 0.8747 | 0.0405 | 0.0000 | -0.2064 | 0.0522 | 0.0001 | -0.2089 | 0.0380 | 0.0000 |
| Adj. $R^2$ | 0.274 | – | – | 0.276 | – | – | 0.261 | – | – | 0.261 | – | – |
| DW | 2.00 | – | – | 2.00 | – | – | 2.00 | – | – | 1.99 | – | – |
| SC | -6.70 | – | – | -6.74 | – | – | -6.68 | – | – | -6.72 | – | – |
| Q($l$=36) | 25.841 | – | 0.6830 | 26.801 | – | 0.6340 | 27.064 | – | 0.6200 | 30.871 | – | 0.4730 |
| LM($l$=5) | 0.7864 | – | 0.5593 | 0.7937 | – | 0.5540 | 0.9385 | – | 0.4546 | 1.3141 | – | 0.2548 |
| LM($l$=10) | 0.6501 | – | 0.7715 | 0.6349 | – | 0.7850 | 0.7489 | – | 0.6786 | 1.0768 | – | 0.3762 |
| LM($l$=15) | 0.8394 | – | 0.6339 | 0.8597 | – | 0.6103 | 0.7733 | – | 0.7089 | 1.2045 | – | 0.2596 |

Notes: Dependent variables are price and accumulation returns for a full and refined specification, $\mu_0$ is the equation constant; $\gamma_l$ and $\gamma_2$ are the estimated coefficients for the macroeconomic incident equation terms, disaster equation terms are denoted $\beta_{ij}$ where $i$ = 1 (bushfires), 2 (cyclones), 3 (earthquakes), 4 (storms), 5 (floods) and the number of lags (in days) is $j$ = 0, 1, 2, 3, 4, 5, $\rho_1$ $\rho_2$ and $\rho_3$ are autoregressive terms, $\phi$ is the seasonal lag term ($r$ = 10 for price returns and $r$ = 11 for accumulation returns, $\theta_l$ and $\theta_l$ are moving average terms, DW – Durbin-Watson statistic, Schwartz Criterion, Q($l$) is the Ljung-Box Q-statistic where l is the number of lags in days, LM($l$) is the Breusch-Godfrey Lagrange multiplier statistic where $l$ is the number of lags in days.